

The Development of a Predictive Model for Condition-based Maintenance in a Steel Works Hot Strip Mill

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Abstract: A recently developed condition-based maintenance model is described which utilises reliability data combined with condition monitoring measurements to predict the remaining useful life of critical components in a steelworks hot strip mill. The results obtained from several case studies are presented which will show how the model can be used as part of a condition-based maintenance strategy.

Key Words: Condition-based maintenance model; condition monitoring; failure prediction; hot strip mill; life prediction; statistical process control; steel works.

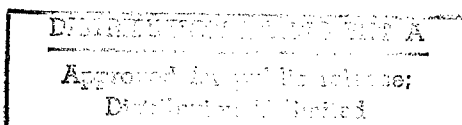
Introduction: In a highly competitive industry, steel works management has to continually focus on achieving increased product performance, quality and efficiency in order to maintain a fair share of the available market and improve its customer base. In an integrated steelworks complex, the hot strip mill is constantly a crucial area of operation in which unscheduled failure or breakdown of machinery can critically affect production down time and associated risk of a reduction in finished goods quality.

For several years, steel companies in the UK have practised condition-based maintenance in strategically vital areas such as the hot strip mill. The methods of monitoring utilised cover virtually the whole spectrum of activity; these include vibration analysis, oil and wear debris analysis, and performance monitoring using numerous techniques to measure, e.g., motor current, temperature, etc.

The present utilisation of these methods enables plant maintenance personnel to detect and also, very often, diagnose pending failure of equipment. What they are unable to do with much certainty is to predict the remaining useful life of failing components.

The predictive model described in this paper has been developed on the assumption that the failure pattern can be divided into two distinct phases: stable and unstable, which can be distinguished by using statistical process control methods. Depending on the way in which the machinery progresses to failure, one of two methods is employed to predict the remaining machine life. The first is based entirely on a reliability model, while the second method uses a novel combination of reliability and condition monitoring measurements to narrow down the time to failure 'window'.

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After describing the methodology used to generate the predictive model, the results of several case studies will be presented which will serve to show how it can be utilised as part of a condition-based maintenance strategy on the hot strip mill.

Development of a prediction model theory:

a) Some basic aspects

For the purpose of identifying that a potential failure problem exists in the hot strip mill, normal alarm limits are utilised on which the levels are periodically adjusted based on factors such as: operational experience, machine supplier recommendations, previous failure data, or national/international standards. The problems imposed by reliance on these methods is that if the alarm limits are set too high, the machine may fail without sufficient advanced warning. If the limits are set too low, the machine will generate false alarms that can obscure a true warning until it is too late. Experienced machine operators and maintenance personnel learn from experience how to distinguish between false and true alarms. However, to try and mimic such experience through the development of a model to predict failure is beset by a number of difficulties.

Some of these difficulties may be addressed by employing a statistical process control (SPC) approach which can be utilised to distinguish data in terms of stable or unstable regions by setting suitable alarm limits. This requires the observation of at least 30 data points and from which, the number of false alarms is expected to be reduced. However, this is machine and process dependent and needs to be conducted for each individual situation. It is, therefore, a time-consuming activity which may be alleviated to some extent by comparing measurements for a group of otherwise similar machines, thereby providing a larger population of failures from which to extract data and establish realistic alarm limits.

Cumulative Summation (CuSum) is a well known, sensitive method used to identify small changes in the average value of a data set. It is also a useful technique for smoothing data and enhancing any fundamental changes occurring in the process characteristics. Similar to SPC control limits, a 'v-mask' can be constructed using the CuSum data to identify when a process is getting 'out of control'.

In predicting the remaining useful life of a machine, previously developed models have based their approach on the extensive use of reliability data coupled to a number of simplifying models [1][2][3]. However, although the prediction is seldom precise enough to be useful for predicting the remaining life of individual machinery, they have been found to be useful for optimising maintenance strategies.

A commonly encountered reliability model applied to repairable systems is the Renewal Process. It assumes: i) that when a machine fails, it is repaired perfectly; i.e., 'As good as new', and ii) that times between failure are independent and identically distributed. When these assumptions hold true, the process is said to be *stationary* and a reliability model can be easily constructed. A special case of the Renewal Process is when inter-arrival times are independently and exponentially distributed with a constant failure rate. This is known as the Homogenous Poisson Process. It is known that the probability of some arbitrary number of failures exhibit a Poisson distribution.

However, in practice, the time to failure is generally a function of many variables, including: design, operating conditions, environment, quality of repairs, etc. It follows,

therefore, that failure times are neither independent nor identically distributed and hence, the Renewal Process is very limited in its scope for application in this area.

All the above models use a single distribution function for all the times to failure over the entire life of the system. This will not be the case, since changes due to deterioration or improvement cannot be modelled by a single distribution function [4]. Hence, a stochastic point process for a repairable system would seem to be a more appropriate approach to adopt.

Christer and Waller [1] present a general methodology for modelling planned maintenance in which they introduce the concept of delay time analysis to model failure detection such that the time period is estimated from when a fault is detected to the point of ultimate failure. However, they found that reliability data was unsuited to this approach and a questionnaire was used in conjunction with human (i.e., the manager's) judgement in order to successfully optimise the preventive maintenance system at that particular location.

Weibull analysis has proved to be a powerful tool in establishing reliability - based diagnosis, from which distinctions can be drawn between infant mortality, random failure and wear-out conditions of machinery. Using reliability data to predict the performance of the machine generally involves assuming that the historical performance will reflect the current performance. The latter is best measured by strategic use of machinery health monitoring techniques. Therefore, the best way to utilise this information to predict failures is by intelligent use of predetermined alarm limits. An example of the kind of approach that can be adopted comes from the aerospace industry where so much of the leading edge maintenance technology has been developed in recent years. Initially, a deterministic model was derived, but it proved to be ineffective for indicating whether an engine should be overhauled or left in service. Sarma et al [5] derived a stochastic model which incorporated sample and noise measurement. This new model proved more successful in identifying problems and formed the basis of a decision process that indicated whether an engine should remain in operation. More recently, Pulkkien [6], developed a mathematical model of wear prediction in conjunction with monitoring the condition of a single component.

A proportional hazard model has been developed, by Knapp and Wang [7], which predicts the remaining time to failure of a machine. It uses a baseline hazard rate, stated as a function of time, and a hazard function based on the machine condition variables. Upon determining the hazard rate, the reliability of the machine is estimated over the subsequent time period from the current sample point.

From the above description of some relevant developments, it is evident that two models are required: one to describe how the component deteriorates; the other to relate the degree of deterioration in the 'condition' of the equipment being monitored.

b) Prediction model theory

The first part of the model relates to ensuring the earliest identification of a problem. From analysis of numerous failure data on the hot strip mill, a general failure pattern becomes apparent which takes the form shown in Figure 1.

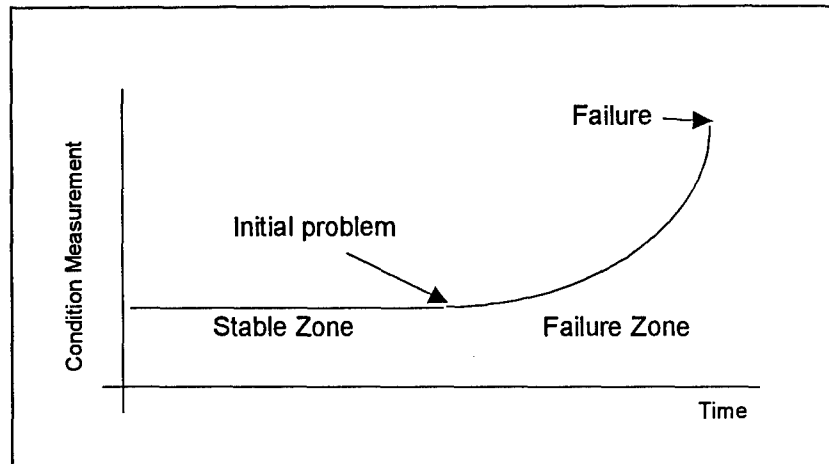


Figure 1: General Failure Pattern

In the 'stable zone', measurements are simply varying about an average value. The variance may be due to process changes between successive measurements and/or measurement error. When the measurements start to deviate from these values, it becomes apparent that a problem exists and the machine may have entered the 'failure zone'. The setting of realistic alarm limits is achieved using SPC theory, such that when the condition monitoring measurements move outside the limits imposed, (normally set at three standard deviations about the average) the condition is registered as being 'unstable' and the operation has entered the designated failure zone.

'Remaining life' models based solely on reliability theory are related to time-based estimates from a new (or repaired) machine condition. If the measurement of a machine's condition is now included, the overall failure time is estimated in terms of detection (reliability) and failure prediction (reliability plus condition monitoring).

In quantifiable terms, by using a Weibull distribution function, we obtain:

For the stable zone:

$$TTF = c_1 [-\ln\{1 - F(t)\}]^{\frac{1}{m_1}} + c_2 [-\ln\{1 - F(t)\}]^{\frac{1}{m_2}} - t \quad (1)$$

For the failure zone:

$$TTF = c_2 [-\ln\{1 - F(t)\}]^{\frac{1}{m_2}} - t_2 \quad (2)$$

Each zone is defined in terms of whether the condition monitoring measurement is inside or outside the alarm limits.

On this basis, it is evident that the 'condition' data acts as 'switch' or 'go/no go' signal in moving from equation 1 to equation 2. However, in order to make further use of the condition data, a model of the failure zone pattern is also introduced. This is depicted in Figure 2.

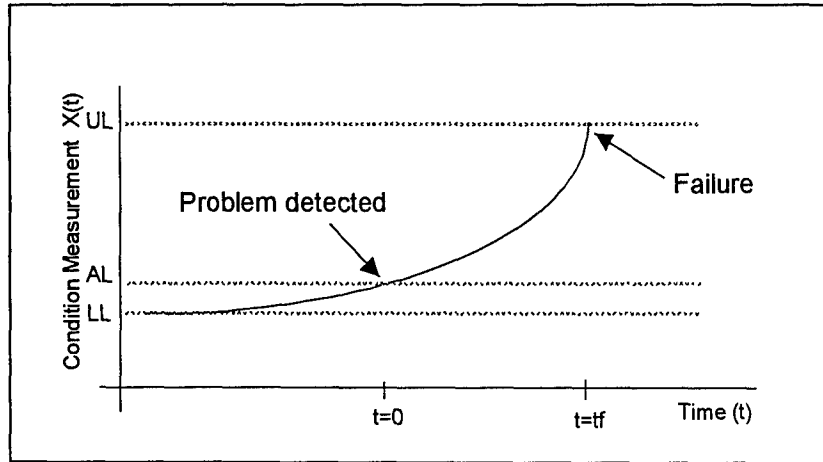


Figure 2: Failure Zone Model

The failure condition commences at the lower limit (LL), which is the averaged conditional value within the stable zone. The condition measurement ($X(t)$) increases until it is detected passing through the alarm limit (AL). Subsequently, at some time, $t = t_f$, the upper limit is reached (UL) and the machine needs to be inspected or withdrawn from service.

Inspection of actual failure case histories revealed that the failure pattern could be approximated to an exponential curve. While this behaviour cannot be said to apply to every situation, it nevertheless serves as an initial starting point for developing the prediction model. Later, a wider spectrum of failure pattern will be introduced and the model will be adjusted accordingly.

Proceeding on this basis, the failure zone is expressed as :

$$X(t) = LL + (AL - LL) \exp \frac{\ln \left[\frac{UL - LL}{AL - LL} \right]}{t_f} \times t \quad (3)$$

Values for LL and AL are obtained from the SPC modelling of the stable zone. The estimate of UL is more problematical since it is the maximum possible level the machine is permitted to reach before actual failure occurs. UL must, therefore, be estimated using appropriate information available either from within the company, or from outside sources, such as equipment suppliers, or by reference to universal standards. The time ' t_f ' is obtained by reference to reliability analysis of previous 'failures', and is, therefore, obtained directly from Equation 2. By rearranging Equation 3, an expression for ' t ' is obtained with respect to the measured condition of the machine.

Hence, the remaining life, after entering the failure zone, is

$$TTF = t_f - t \quad (4)$$

By further substituting the values of ' t ' and ' t_f ', we obtain:

$$TTF = c_2 \left[-\ln \{ 1 - F(t) \} \right]^{\frac{1}{m_2}} \times \left[1 - \frac{\ln \left[\frac{X(t) - LL}{AL - LL} \right]}{\ln \left[\frac{UL - LL}{AL - LL} \right]} \right] \quad (5)$$

To summarise: in order to predict the remaining life of the machine, Equation 1 is used while the condition monitoring measurements lie within the pre-set alarm limits; i.e., in the stable zone. When the condition monitoring measurements indicate that a problem has occurred, i.e., entered the failure zone, Equation 5 is utilised, in which the time to failure is predicted using a combination of reliability and condition monitoring measurements.

To best illustrate the way in which the model is designed to function a computer program was written to simulate typical machine failure patterns of the type observed to occur frequently in the hot strip mill. The simulated machine failure pattern comprised a stable zone of, on average, 20 weeks duration, followed by a failure zone which was also an average of 20 weeks. The effect on the prediction of varying the time was also assessed, and Figures 3, 4 & 5 show the results obtained for three different conditions. In Figure 3, an ideal failure pattern is demonstrated. In the stable zone, a wide distribution is obtained which reflects the uncertainty which accompanies sole dependence on reliability data. In the failure zone, the prediction rapidly becomes much more narrow and focused, eventually identifying the failure time as being 40 weeks from start with a very high certainty, depicted by the increased 'sharpness' of the distribution peak. The nearer the time approaches the actual failure time, the more certain is the prediction.

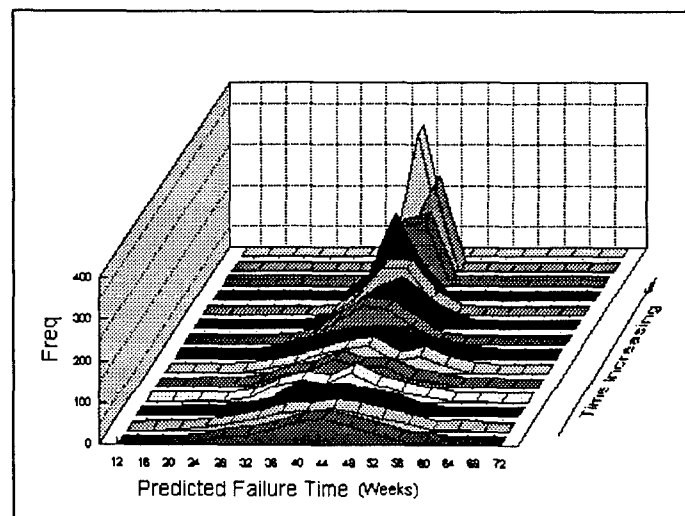


Figure 3: Illustrating an ideal failure pattern at 40 weeks

In Figure 4, the machine experiences a much shorter failure zone of 10 weeks, in which it is evident that the model 'tracks' the time to failure (~ 30 weeks) as the later condition monitoring measurements are also used.

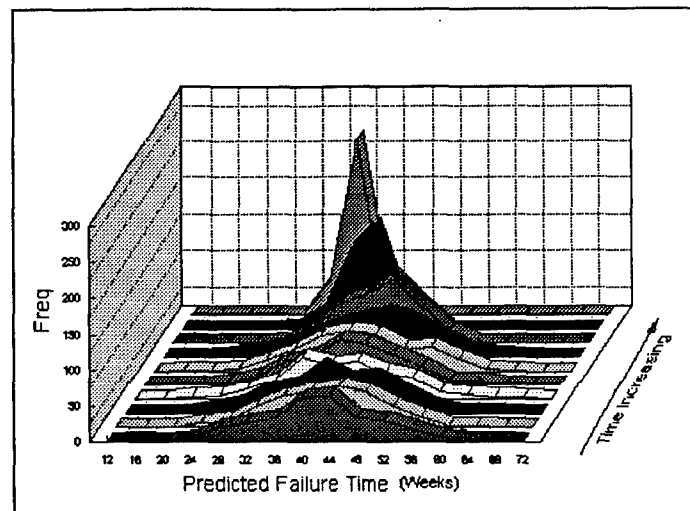


Figure 4: Illustrating a shorter failure zone, failure at 30 weeks

If the stable zone time also deviates from the ideal average time, a 'step' jump is observed to occur in the prediction distributions, as is demonstrated in Figure 5 in which the stable zone only lasts for a period of 10 weeks. Once again, in the failure zone, the model tracks to the point of failure after 50 weeks.

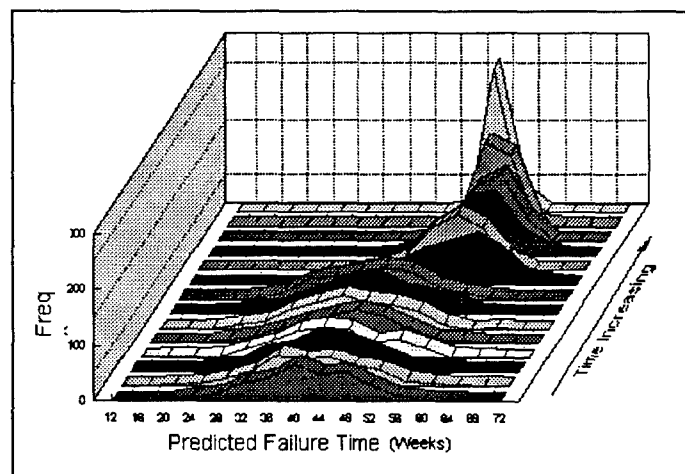


Figure 5: Illustrating a longer stable zone time, failure at 50 weeks

Case Studies: A number of hydraulic pumps located on the hot strip mill, and subjected to regular condition monitoring using vibration analysis, were selected for an initial case study.

The present condition monitoring methods and strategies used on the mill are generally very effective in identifying pumps which require attention before a catastrophic failure occurs. However, no method currently exists for predicting the remaining useful life of the pumps while they are still in operation. The condition monitoring data used in this study is based solely on the measurement of overall vibration level.

The machine group selected for the initial assessment comprised three double vane pumps. Each delivering 320 litres per minute of hydraulic fluid at 160 Bar pressure. The pumps are each driven by a 120 kW electric motor at 1485 rev/min. The system supplies the

hydraulic requirements to critical machinery, including the Reversing Rougher, Vertical and Horizontal Scale Breakers.

SPC analysis of the stable measurements resulted in an average condition measurement value of 6 mm/s and an estimated alarm level of 9.5mm/s. Subsequent Weibull analysis revealed that the distribution approximates to a normal distribution with an average stable region time of 260 days. The general failure pattern approximated well to an exponential curve and, as a result, the upper limit was set at 18mm/s. The resulting time from first detection to reaching the upper limit of 18mm/s was averaged out at 104 days. The distributions for all three pumps are presented in Figures 6, 7 & 8. For pump No.1, the condition monitoring measurements only provided sufficient warning to prevent catastrophic failure, although the last measurement taken did pin-point correctly the failure time.

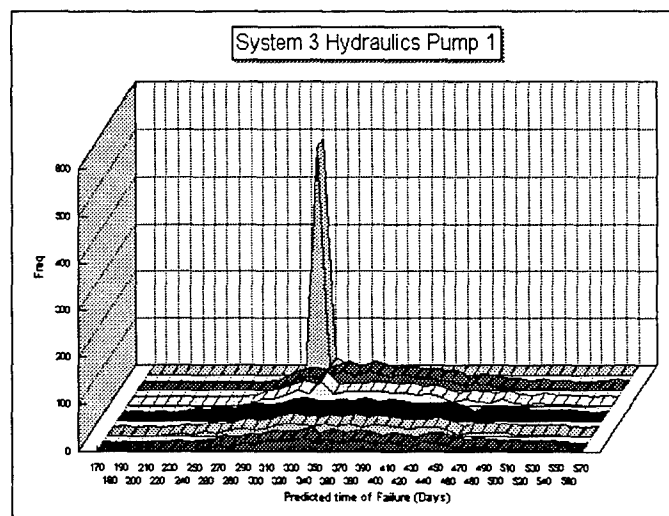


Figure 6: Showing Pump 1 failure predictions

In the case of Pump No.2, there was sufficient data available to provide a more focused prediction of time to failure.

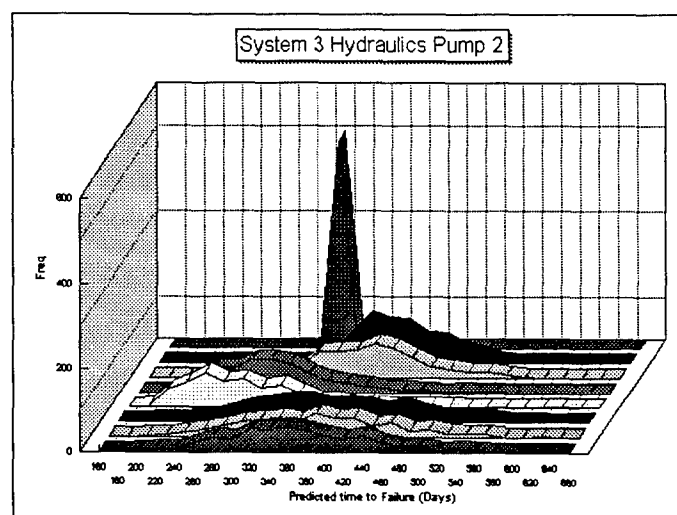


Figure 7: Showing Pump 2 failure predictions

Pump No. 3 failed with a relatively clear failure pattern which is reflected in an accurate prediction to time to failure from an early stage.

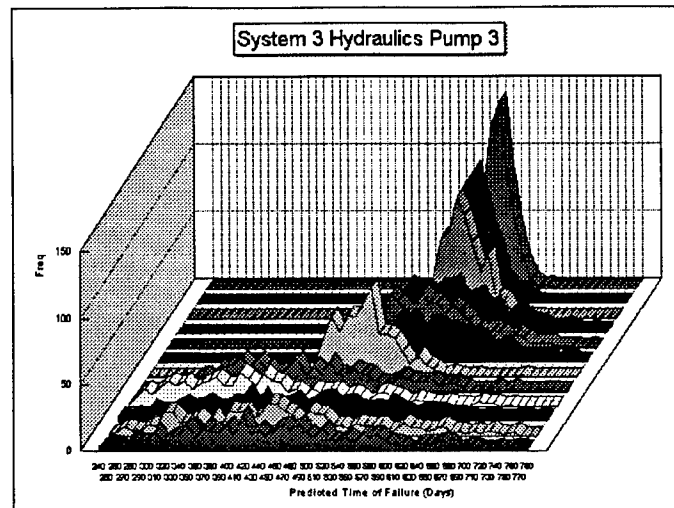


Figure 8: Showing Pump 3 failure predictions

Regarding the matter of deciding the alarm limits; initially, all three methods for detecting a machine problem were used. In the stable region, the measurements were well within the normal alarm limits, but when the measurements were closer to these limits, quite a large number of false alarms were observed; accounting for about 10% of the total number of measurements. By changing to the limits set using SPC, the number reduced to 5%. Using CuSum analysis resulted in a further improvement to only 2.5% false alarms. However, in the failure zone, the CUSum method led to large variation in the measurements which made it difficult to estimate properly the average level and associated distribution. CuSum was, therefore, judged to be best utilised in identifying when the machine problem first occurred. SPC analysis in this zone maintained the level of false alarms, but at the expense of reduced reaction time to failure. Using the normal limits still resulted in a higher percentage of false alarms but it indicated a failure slightly sooner than the SPC analysis.

Conclusions: Currently in industry, condition monitoring can identify when machine problems are occurring and, given enough experience, pin point the exact cause. However, it is more difficult to predict the remaining life of the machine once the problem has been identified and therefore when to change or maintain the machine.

Current literature on remaining life prediction has focused on solely reliability based or mathematically complex models. There is clearly a need for a simple, systematic prediction model readily applicable to the industrial situation.

This paper has attempted to introduce such a model. Condition monitored measurements have been divided into two regions; a stable and failure zone. Whilst in the stable zone, condition measurements are normal and hence a reliability based model is utilised. When condition measurements increase, indicating a potential problem, reliability and condition monitoring information is used to form the remaining machine life prediction.

A case study was carried out to test the model. Initial results were encouraging with all machine failures being predicted before they failed. It was evident that the prediction model was dependent on the quality and accuracy of the condition monitored measurements.

It is anticipated the model will be applicable to most condition monitored situations provided that the failure lead time is sufficiently long and the condition monitoring reflects the health of the machine.

References:

- [1] A.H. CHRISTER & W.M. WALLER: "An operational research approach to planned maintenance: Modelling PM for a vehicle fleet", *Journal of Operational Research Society*, Vol. 35, No. 11, 1984, pp 967 - 984.
- [2] A.H. CHRISTER, W. WANG, J. SHARP, R.A. BAKER: "A pilot study on maintenance strategy of finishing mill roll change equipment at Llanwern, British Steel", *University of Salford*, 13 November 1995.
- [3] H. ASHER and H. FEINGOLD: "Repairable systems reliability", *Marcel Dekker inc.*, 1984.
- [4] L.C. TANG & F.O. OLORUNNIWO: "A maintenance model for repairable systems", *Reliability Engineering and Safety Systems*, Vol. 24, 1989, pp 21 - 32.
- [5] V.V.S. SARMA, K.V. KUNHIKRISHNAN & K. RAMCHAND: "A decision theory model for health monitoring of aeroengines", *Journal of Aircraft*, Vol. 16, No. 3, 1979, pp 222 - 224.
- [6] U. PULKKINEN: "A stochastic model for wear prediction through condition monitoring", *Operational Reliability and Systematic Maintenance*, pp 223 - 243.
- [7] G.M. KNAPP & H.P. WANG: "Automated tactical maintenance planning based on machine monitoring", *International Journal of Production Research*, 1996, Vol. 34, No. 3, pp 753 - 765.

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